Performance Matrix

- Confusion matrix
- Accuracy
- Precision
- Recall
- F - beta score.

Confusion matrix:

Consider following dataset:

feature 1	feature 2	o/p (y_i)	$\hat{y}_i$	
–	–	1	0	F.P
–	–	0	1	F.N
–	–	0	0	T.N
–	–	1	1	T.P
–	–	1	1	T.P
–	–	0	1	F.N
–	–	0	0	T.N
–	–	1	0	F.P
–	–	1	1	T.P
–	–	0	0	T.N

Drawing confusion matrix based on above data:

← Predicted $(\hat{y}_i)$ ↓ / Actual (y_i) →	1	0
1	T.P [True positive] # This quadrant represent (1,1) position mean actual and predicted value match ~~eth~~ eachother. we count & sum total no.s of such out come. for positive O/P 3	F.P [False Positive] # This quadrant represent (0,1) position means in actual output is not matched with predicted or prediction is made wrong. we put sum of total such out come here. we count result where actual it's 0 but prediction is giving 1. 2
0	F.N [False Negative] # This quadrant represent (1,0) position count out come where actual we have output but in prediction we are getting none. we count such outcome. 2	T.N [True Negative] # This is (0,0) quadrant we count those out comes where both actual and predicted data points are 0 means both are false. 3

Considering above T.P, F.P, F.N and T.N let mention same in the data for clarity of previous page.

Accuracy matrix:

$$Acc : \frac{T.P + T.N}{T.P + T.N + F.P + F.N}$$

Putting values in above formulae to find accuracy:

$$Acc = \frac{3 + 3}{3 + 3 + 2 + 2} = \frac{6}{10} = .6$$

$\Rightarrow$ 60% accuracy.

Precision :

$$\frac{TP}{TP + FP}$$

Putting values to find precision:

$$\frac{3}{3 + 2} = \frac{3}{5}$$

Recall :

$$\frac{TP}{TP + F.N}$$

Putting values to find Recall:

$$\frac{3}{3 + 2} = \frac{3}{5}$$

F. beta score:

$$(1+\beta^2)\ \frac{\text{Precision} \times \text{Recall}}{\beta^2 \times \text{Precision} + \text{Recall}}$$

Case I:

when FP and FN are both important

$\beta = 1$

Then, F. beta score:

$$2 \cdot \frac{\text{Precision} \times \text{Recall}}{\cancel{2}\,\text{Precision} + \text{Recall}}$$

$$= \frac{2\,P \cdot R}{\cancel{2}P + R}$$

[P - Precision
R - Recall.]

Case II:

when FP is more important than FN

$\beta = 0.5$

Then, F beta score:

$$= \frac{1.25\,P \cdot R}{.25P + R}$$

Case III :

when F.N is more important than F.P, $\beta = 2$

$$F.2 \text{ Score} = \frac{5 P \times R}{4P + R}$$

Support Vector Machines (SVM)

SVC - Support Vector Classifier.
(Classification problem)

SVR - Support Vector Regression.
(Regression problem)

Equation of line be:

$$y = mx + c$$

In linear reg:

$$\hat{y}_i = \beta_0 + \beta_1 . x$$

also, $ax + by + c = 0$ [st. line equation]

from above :

$$\boxed{y = \underbrace{-\frac{a}{b}}_{\text{Coefficient}} x \;\; \underbrace{-\frac{c}{b}}_{\text{Intercept}}}$$

Now, above equ. can also be written as :

Above equation can be written as :

$$w_1 x_1 + w_2 x_2 + C = 0$$

Also,

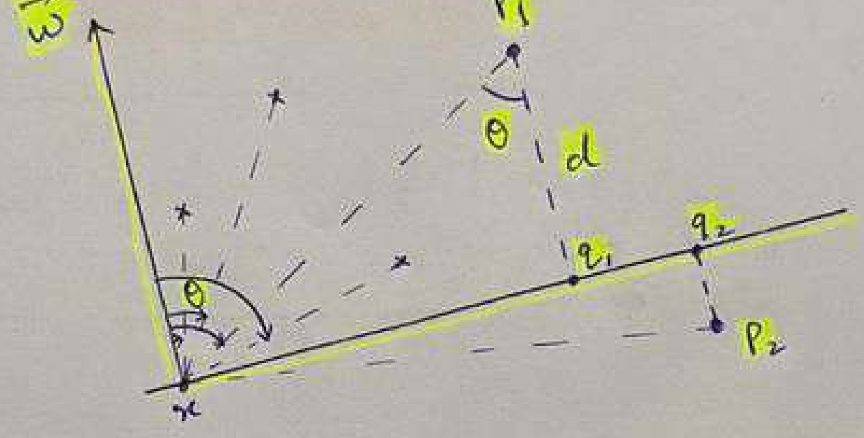
$$w^T . x = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} [x_1 \;\; x_2]$$

$$= w_1 x_1 + w_2 x_2$$

Thus, we can write above equ. as :

$$w^T . x + c = 0$$

Consider line in 2-D with vector $\vec{w}$ perpendicular on it.



Consider random point P_1 & P_2 on both side of the line.

q_1 & q_2 is the point of intersection of P_1 & P_2 point $\perp$ to the line with the line. θ is the $\angle$s b/w the $\vec{w}$ and the line connecting point x to the corresponding datapoint. As of now consider θ for the point P_1

$$\boxed{\text{Now, } d = \frac{w^T \times P_1}{|w|}}$$

$\left[w \cdot^T P_1 : |w| \, |P_1| \cos\theta \right]$

when the datapoints are in the direction of the vector $\vec{w}$ value of $\cos\theta$ is +ive because θ lies b/w 0 to 90. For points in opposite direction value is -ive as θ lies b/w 90° to 180°.

$$\boxed{\text{Thus, } d = |P_1| \cos\theta}$$

For :

$\theta \rightarrow 0 - 90^\circ \rightarrow d = $ +ive

$\theta \rightarrow 90^\circ - 180^\circ \rightarrow d = $ -ive

d is the distance of the point from the plane. [It's minimum distance from the line & thus also $\perp$]